

# Heritage and Innovation of Art Creation in the Context of Big Data and Public Health Events

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**Abstract:** In the context of big data of public health events, the inheritance and innovation of fine art creation becomes a new opportunity and challenge. In this paper, based on the art image data collection, we establish a convolutional neural network model with migration learning and inverse algorithm for the recognition of art creation under the big data of public health events. The experimental results show that the visual image analysis algorithm can classify paintings with an accuracy of more than 99%, which has good painting recognition effect and classification ability. The migration learning model achieves a training accuracy of over 97% at 50 training rounds and also performs well on the test set with an accuracy of 96.97%. Using the neural network model of art creation established in this paper for intelligent innovation of art images, with the increase of model settings, it can guarantee the recognition of art creation images between 60% and 80%, and with the increase of iterations, the effective linearity keeps stabilizing and the innovation rate keeps increasing, up to 79.0%. In this paper, the established methods are introduced into Lenet-s model, GoogleNet model and ResNet model for experiments, and it can be seen that the training sets1 of the three models have greater than or equal to 99.8%, 99.6% and 99.4%, respectively, and the training sets2 of the three models have 99.4%, 99.2% and 99.4%, respectively, which proves the neural network model of this paper validity.

**Keywords:** public health events; art creation; big data; neural networks; migration learning

## 1. Introduction

In the context of the era of big data, the three-dimensional development of public health events and management systems in China requires the comprehensive consideration of multiple factors, such as relevant policies, management models, the degree of implementation, and publicity models (which include art creation and publicity, etc.), which are an important background support to ensure the development of national life and an important basis for the growth and realization of a happy life for each individual [1]. Therefore, health is a prerequisite for the development of all productive life of the nation and a necessary condition for the prosperity of all national undertakings [2]. According to the Health China strategy, health is not only about physical health, but also about mental health and emotional health, and the best way to achieve health is not only passive treatment by "treating existing diseases", but also active prevention by "treating future diseases". Public health emergencies are unknown, difficult to prevent and control, and of high concern, so the importance of publicity is particularly important [3-5] Isolation is a good remedy to effectively prevent the expansion of public health emergencies. Emerging digital technologies, such as big data and artificial intelligence, have promoted the vigorous integration and development of various fields. In today's era, when public health events occur frequently, the processing of public health information in the form of digital graphic technology and new art propaganda [6-7] has effectively promoted joint prevention and control and mass prevention and treatment. In addition, convolutional neural networks (CNN) [8] have become a very advanced computer vision tool in industry and academia. In addition to "traditional" computer vision tasks such as image classification and object localization, convolutional neural networks have been widely used in many fields such as facial recognition [9] and autonomous vehicle driving [10]. Deep convolutional neural networks are trained to distinguish between "content" and "style" in images [11]. Reinforcement learning has a long history of research, dating back to the middle of the 20th century - the Bellman equation proposed by Professor Bellman [13-16]. Hausknecht et al [17] proposed the DRQN algorithm, which replaces the fully connected layer of DQN with recurrent neural network and can better handle the missing information. In 2016, Wang et al [18] proposed the Dueling-DQN algorithm to optimize the internal of DQN framework and better results in performance evaluation. In

the same year, DeepMind proposed the AlphaGo algorithm [19], which mainly utilizes Monte Carlo tree search and deep learning techniques, and then learns Go games through human prior knowledge, and soon AlphaGo defeated the Go master Lee Sedol, attracting widespread attention from the world.

As research continues, reinforcement learning is gradually applied to the more complex multi-intelligence domain. Tammou et al [20-23] proposed the IDQN algorithm, which is the most direct extension of DQN in the multi-intelligence direction, and which allows any one intelligences to treat other intelligences as part of the environment. Yao et al [24] proposed the SMIX( $\lambda$ ) method, which replaces the 1-step Q-learning goal with a SARSA( $\lambda$ ) goal, eventually learning a stable and generalizable joint action value function. In 2019, Wang et al [25] introduced a message-passing mechanism based on QMIX, in which the intelligences act alone most of the time and occasionally send messages to other intelligences to share their intentions in the current state.

In this paper, we focus on the problems of multi-intelligence reinforcement learning that have not been thoroughly studied and not yet covered, mainly in the context of public health events such as the New Crown epidemic. In addition, in order to solve the problem that the Transformer model cannot be applied due to its huge number of parameters, as shown in Figure 1, this paper proposes a lightweight network, called FuseNet, which combines the local representation of convolution and the global representation feature of Transformer model.

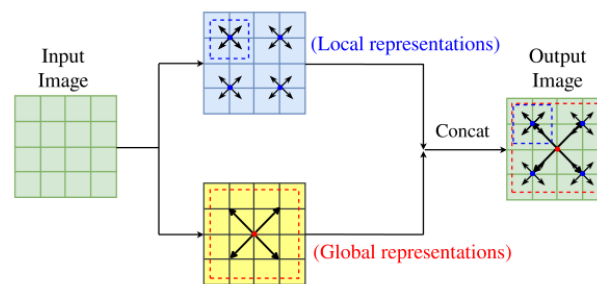


Figure 1: Schematic representation of the fusion of local and global representation models

## 2. Experimental data creation

### 2.1 Fine art image data acquisition

Experimental data from the following three ways: ① the use of effective pixels  $\geq 2.07$  million camcorder, imager 3 pieces  $\geq 1/2.8$ -inch CMOS sensor, the acquisition of fine art images; ② the use of camcorder combined with a computer to process the image data in the context of public health events; ③ run Python crawler code from the search for the basic characteristics of art creation network images under big data. The obtained images were annotated with the data under the guidance of experts, and a total of 1264 valid data were obtained. Five categories with the largest amount of data were selected from the valid data: comic strips, watercolor paintings, sketches, and Chinese paintings, and the number of each category was 70~90 as the experimental data, and some of the fine art images are shown in Figure 2.



Figure 2: Example of 4 types of important art image data in the context of a public health event

## 2.2 Image data pre-processing

The resolution of the images selected by the network is very different from that of the ripped and filmed images. For this reason, the data images are first normalized to  $224 \times 224 \times 3$  by normalization process, and the image data are divided into training and test sets according to the 7:1 ratio. In order to increase the data volume, data enhancement is performed for the training part of the images, mainly applying rotation transform (rotation angle  $90^\circ$ ,  $180^\circ$ ,  $270^\circ$ ), mirror transform and translation transform to preserve as much information of the images as possible. The translation transform is to add the specified horizontal and vertical offsets to all the pixel coordinates of the image, and the horizontal and vertical translations of the pixel  $(x, y)$  are  $x_0$  and  $y_0$  respectively, then the pixel coordinates after translation are

$$\begin{bmatrix} a(x, y) \\ b(x, y) \\ 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & x_0 \\ 0 & 1 & y_0 \\ 0 & 0 & 1 \end{bmatrix}$$

The rotational transformation rotates the original image clockwise around the origin by an angle of  $\theta$ . The pixel coordinates after the rotational transformation are

$$\begin{bmatrix} a(x, y) \\ b(x, y) \\ 1 \end{bmatrix} = \begin{bmatrix} \cos(\beta) & -\sin(\beta) & x_0 \\ \sin(\beta) & \cos(\beta) & y_0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

The flow chart shown in Figure 3 shows the inverted residual bottleneck structure in CoAtNe. Unlike MBConv, a maximum pooling downsampling layer and a normal convolutional layer with a convolutional kernel size of 1 are used in the residual path to further improve the feature extraction capability of MBConv. In this paper, the proposed FuseNet convolutional feature extraction module for processing local information in the pre-stage is based on the inverted residual bottleneck structure in CoAtNet.

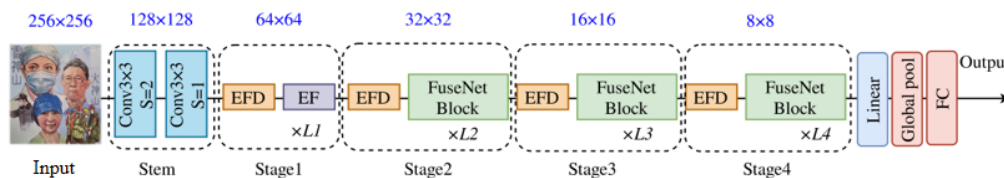


Figure 3: Important art image data feature extraction process

## 3. Analysis of model training and experimental results

### 3.1 Test environment

The experimental environment is win7 64-bit; the processor is Intel(R) Core(TM) i5-4210U CPU @1.70 GHz 2.40 GHz; the IDE is Pycharm 2018.1.4; the libraries are TensorFlow 1.7.0, Keras 2.2.4, numpy 1.14.6, open-python 4.0.0.21. Open-python 4.0.0.21.

### 3.2 Experimental results and analysis

The number of training rounds for each of the five trials is set to 80 in the code, and the value of the loss function is monitored in real time using the "Early Stopping" function, and the training is terminated early when the loss function does not decrease after 30 fine adjustments. The recognition accuracy is used as the main reference index, and the model is evaluated by the auxiliary indexes such as convergence speed and overfitting. Figure 4 shows the training and testing accuracies under the influence of the number of training rounds.

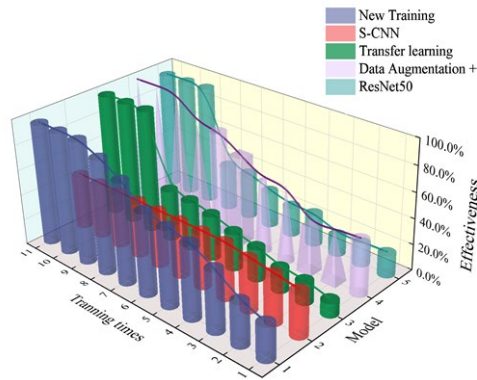


Figure 4: The training and testing accuracies based on models

The S-CNN model with only four convolutional layers maintains a training accuracy below 45% for 80 epochs, because the network is too shallow to fully learn the deep features. ResNet50, which has the most convolutional layers, has a training accuracy of 99% at 20 epochs, which is not suitable for image recognition tasks with small sample data sets. The migration learning model achieves over 97% training accuracy in 50 training rounds and also performs well in the test set with 96.97% accuracy.

It can be seen that with the increase of model setting, it can guarantee the image recognition and innovation between 60% and 80%, and with the increase of iterations, the effective linearity tends to be stable continuously in Figure 5. The number of points increases and the rate of art innovation design keeps increasing up to 79.0%, thus effectively ensuring the effectiveness of the neural network model.

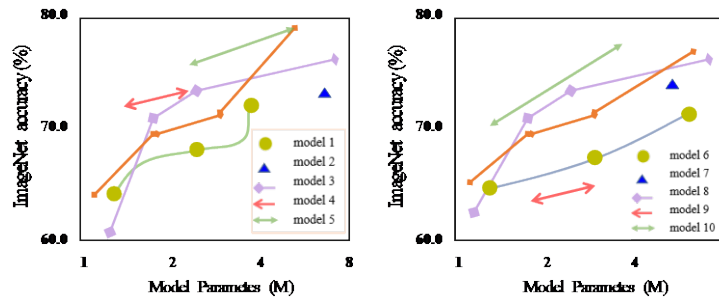


Figure 5: Recognition rate of three applied models for two datasets

In this paper, the established methods are introduced into Lenet-s model, GoogleNet model and ResNet model for experiments, and the number of network layers of the three models are 7, 22 and 152 layers respectively, and the identification of the data set is shown in Figure 6 which can the training set 1 of the three models have greater than or equal to 99.8%, 99.6% and 99.4% respectively, and the training set 2 of the three models have 99.4%, 99.2%, 99.4%, proving that the method of this paper has a very high recognition accuracy, which can provide important support for the inheritance and innovation of art creation in the context of public health events.

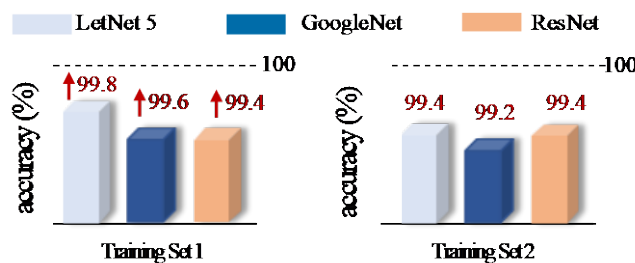


Figure 6: Recognition rates of three applied models for two datasets

#### 4. Summary

In this paper, we combine convolutional neural network model of inverse algorithm on the basis of fine art image data acquisition and apply the method based on shared parameters in migration learning

for the recognition of fine art creation under big data of public health events. Realizing the use of computer for painting the paintings are identified and classified, as well as the subsequent transmission and innovation.

The experimental results show that the visual image analysis algorithm classifies paintings with an accuracy of more than 99% and has good painting recognition effect and classification ability. It is feasible for recognizing visual arts with different painting segmentation. However, there are still some shortcomings in this paper, due to the diverse styles of art paintings and the increasing number of samples and forms of paintings included in the training set. The recognition ability of painting styles is sufficient.

Using the neural network model of fine art creation established in this paper for intelligent innovation of fine art images, with the increase of model settings, the effective recognition of fine art images can be guaranteed between 60%-80% of image recognition and innovation, and with the increase of iterations, the effective linearity keeps stabilizing, the number of points increases, and the rate of fine art innovation keeps increasing, which can reach up to 79.0%, thus effectively ensuring the effectiveness of the neural network model.

It can be seen that the training sets1 of the three models have greater than or equal to 99.8%, 99.6%, and 99.4%, respectively, and the training sets2 of the three models have 99.4%, 99.2%, and 99.4%, respectively, proving that the neural network model of this paper can provide an important reference basis for the heritage and innovation of art creation in the context of public health events.

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